MEDICAL OUT-OF-POCKET EXPENDITURES
AND
ALTERNATIVE POVERTY MEASURES

BY

BRETT O'HARA AND PAT DOYLE[1]
U.S. CENSUS BUREAU

Poverty Measurement Working Paper

---

[1] This paper reports the results of research and analysis undertaken by Census Bureau staff. It has undergone a Census Bureau review more limited in scope than that given to official Census Bureau publications. This report is released to inform interested parties of ongoing research and to encourage discussion of work in progress. Please contact Brian.J.Ohara@census.gov for any questions.

MEDICAL OUT-OF-POCKET EXPENDITURES AND ALTERNATIVE POVERTY MEASURES

Abstract

The impact of medical out-of-pocket expenses (MOOP) on alternative poverty rates is estimated in this paper. Different types of imputations based on data from the Medical Expenditure Survey and the Consumer Expenditure Survey are used to determine the quality of the reported amount of MOOP in the Survey of Income and Program Participation. Comparisons are made of the imputation for MOOP by focusing on the average dollar amount imputed to families and the resultant growth in poverty. Significant differences were found depending on the imputation approach. Overall, the reported MOOP value in the Survey of Income and Program Participation performed better than expected.

Key Words: Medical Expenditures, Poverty, Imputation

I. Introduction

Out-of-pocket medical expenses (MOOP) can cause a low-income family to feel impoverished even though the official definition of poverty indicates that they are not poor. Bankruptcy studies confirm the tremendous burden that medical expenses can have on a family. Depending on the study, medical expenses are the third largest cause of bankruptcy when listed as the reason for financial hardship and the first cause of bankruptcy when indirect effects are factored in such as the loss of job due to medical problems (Sullivan et al 2001). Because of MOOP, the income available to a family may be less than that of people that are officially poor. This paper investigates this possible disconnect between total family income and the resources available to the family after accounting for MOOP.

Alternative poverty measures focus on available resources to the family; we modify these resources by deducting family MOOP from family income. The official poverty thresholds are used in this analysis. A family is in poverty when family resources (total family income minus family MOOP) are less than the appropriate poverty line. This simple modification is used because we are concerned with the marginal effect of MOOP on poverty; our primary concern is the impact of MOOP on well being. Using a simple adjusted poverty rate provides a clear benchmark. Does MOOP push people into poverty or not? What groups of people are impacted the most?

We are also concerned with the idea that a family might feel impoverished because of the expectation of future medical expenses. Future medical risks and past levels of MOOP are closely linked. The same factors that led to high past MOOP influence the expectation of high future MOOP. For instance, a lack of or inadequate health insurance, high medical utilization, poor health or disability can lead to high MOOP and a high risk of future medical expenses.

This paper investigates different ways to calculate MOOP through imputation procedures and its subsequent impact on our simple alternative poverty rate.

II. Literature Review

The National Academy of Sciences (NAS, 1995) Panel on Poverty and Family Assistance made several recommendation concerning alternative poverty rates. Perhaps the most dramatic recommendation was to use the Survey of Income and Program Participation, rather than the Current Population Survey, for alternative poverty measures. Two suggestions concerned medical expenditures directly: Recommendation 4.2 directed that alternative poverty measures should deduct family MOOP from family income before calculating new poverty rates; Recommendation 4.3 suggested that a new measure of economic well being should be produced that encompassed the risk of medical care.

A medical care risk index (MCRI) would be separate from poverty measures because a method to value benefits, such as adequate health insurance, is not feasible (NAS 1995). Although using the same data source for MOOP and an MCRI was not a NAS recommendation, it would have advantages. The information needed to create the MCRI measure included the characteristics of health plans and the likelihood of incurring relatively high out-of-pocket medical costs. Because MOOP and the variables used to create a MCRI are highly correlated, it would be desirable to have the two values created from the same data source for secondary analysis.

Short and Banthin (1995) proposed a measure of the adequacy of insurance coverage. Their approach to measuring the underinsured is useful for producing an MCRI and MOOP. If a person with private health insurance had medical expenditures greater than ten percent of family income, then the person was underinsured. To make this calculation, the authors examined data from the National Medical Expenditure Survey (**NMES**) on health insurance plans and the total expenditures and utilization of medical services. They found that the vulnerability to high medical costs were sensitive to different types of health insurance plans.

Doyle (1997a) discussed a method for adapting Short and Banthin's approach to develop an MCRI. Using NMES, Doyle (1997b) showed that certain imputation techniques could be used to produce an accurate MOOP value with the same method that would be used to create an MCRI. Whether or not the methods in Doyle (1997b) can be replicated using SIPP data is a major thrust of this paper.

We decided not to incorporate other suggestions of the NAS panel because our concern is the impact of MOOP on poverty; the only change to family resources is that MOOP is deducted from family income. Thus, the alternative poverty measure presented here is not intended as a feasible alternative to the official poverty rate.

III. Data

Because MOOP needs to be measured accurately, several data sources and methods are considered. The data on families and individuals was gathered from three sources. The primary source is the Survey of Income and Program Participation (SIPP). Calendar year 1996 data was derived from the 7-Wave Research Longitudinal File. Because the longitudinal weights have not been produced, the December 1996 cross-sectional population weights were used. The SIPP Medical Expenses and Utilization of Health Care Topical Module was used to obtain information on MOOP for adults age 15 or older as well as eight questions on utilization of medical services for all family members. The answers given covered the previous 12 months

The Medical Expenditure Panel Survey (MEPS) is a two-year panel survey with quarterly interviews. In each interview, respondents were asked over a hundred questions concerning different aspects of medical expenses and utilization. However, there is little information on the family's share of health insurance premiums. Therefore, most families only have information on out-of-pocket expenditures for medical services – not total MOOP. The income measures are also not as precise as the SIPP's.

The third source of data is the Consumer Expenditure Survey (CE). It is a fifteen-month survey with quarterly interviews. The respondents are asked sixteen questions on expenses due to medical utilization and additional sixteen questions on reimbursement. For each health insurance policy, the policyholder is asked the family's share of the health insurance policy's cost. Because the CE contains information on out-of-pocket costs for both health insurance and medical utilization, a value for MOOP can be derived for each family.

Of the three data sources used, none is ideal for measuring MOOP. MEPS is the most accurate data source in gathering information on out-of-pocket expense from medical utilization; on a quarterly basis, information is gathered on both large and small amounts of expenses. The many probes and short recall period made it more likely that people would remember both the large and the smaller expenses. The CE has complete information on MOOP and separate information on the cost of the families' share of health insurance premiums. However, CE does not compare well with MEPS in the sheer volume of questions that are asked to encourage the recollection of less obvious or smaller expenses due to medical utilization. SIPP ranks lowest on data quality for MOOP information because of the long recollection period, the low number of probes, and the lack of information on children.

For this study we used a cohort of the population existing for all of 1996. Thus the sample underlying the analysis does not reflect the dynamics of the underlying population during the year. This is consistent with the approach used for measuring poverty in SIPP (Naifeh 1998), although its not optimal for the determination of the impact of MOOP on poverty. In particular, this method of capturing the population omits the impact of MOOP among those who died during the year, a population known to have high total medical expenses.

In addition, the underlying sample for this study is restricted to the SIPP and MEPS sample members present during all the waves that collected information for 1996. The sample weights used represent the U.S. civilian population as of December 1996 (cross-sectional weights). These weights were not adjusted to account for those present in the sample in December 1996 but who did not have data for one or more of the other rounds of interviews.[2] Note the impact of this design choice was to ignore the medical expenses of persons who were born or immigrated into the sample.

IV. Methodology

Imputation techniques are used to establish values and quality of MOOP from different data sources. Appendix A and B discuss the details of these two techniques. One of the MOOP imputations was a model-based estimate using the Betson (2001) approach. Betson's model is currently used to impute family MOOP to the Current Population Survey. At a simple level, a model-based approach uses regression techniques on one data source to form predicted values for a secondary data source. One advantage to this type of imputation is that the estimates of

[2] The number of people dropped from the analysis in MEPS was 707 people because they were not in sample for the entire year. The weighted total associated with these individuals was 7,982,503. The number of people dropped from the analysis in SIPP was 6,989 because they were not in sample for the entire year of 1996 but were in sample in December of 1996. The weighted total associated with these individuals was 17,738,086. The weights were given a simple adjustment to population totals to reflect the people that were dropped. There are no adjustments made to reflect differential attrition rates.

MOOP can be recreated by reading Betson's paper and following the programming code. Betson's model used the CE to predict a value for family MOOP. Using the published regression coefficients, we applied these numbers to the SIPP data source to obtain predicted family MOOP. This predicted MOOP amount for SIPP is referred to as the Betson model in this paper.

The second imputation technique used in this paper is a statistical match. A statistical match uses a data file that has the variable of interest (the donor file) and a primary file that does not have this variable (the recipient file). A match can be made if both files can be made to look similar. This means the files have variables in common that are highly correlated with the donor variable and are of high quality. Once the match is made, using statistical matching software, the donor variable is transferred to the recipient. Statistical matching is the approach recommended by Doyle (1997b) due to the high volume of correlated information needed to be imputed to SIPP in order to produce the MCRI. Campbell and Doyle (2000) showed that the data quality and the distributions of the medical utilization variables across MEPS and SIPP show sufficient similarity to support the statistical match. The value of MOOP that was statistically matched to SIPP is referred to as the Doyle match in this paper.

The third imputation technique used is a predictive mean match. This approach uses a method that lies in-between the Betson and the Doyle imputations. Regression techniques are used to obtain predicted values for both the donor and recipient files. The statistical match first identifies persons with the same predicted MOOP value in the two data sources. The second step identifies persons "who look alike" within this subgroup and donates the actual MOOP value to the observation in the recipient file.

In general, results from the SIPP imputations will be compared to the results using MEPS data. As previously discussed, there is not a perfect measure for MOOP. The following list details the construction of the MOOP amounts that are in the tables. These different values for MOOP are used in our resource definition of poverty: family income minus family MOOP. When resources fall below the poverty threshold, the persons in the family are considered poor.

1) MEPS "Reported"
    i) Reported amount for out-of-pocket expenses from medical services from MEPS
    ii) Imputation of family share of health insurance premiums based on CE data (using a statistical match)
2) SIPP "Reported"
    i) Reported amount of MOOP for people age 15 and older
    ii) Imputation of MOOP for children age 14 and under based on MEPS data (using a statistical match)
3) SIPP Betson
    i) Imputed amount of MOOP from CE (using a regression/model)
4) SIPP Doyle
    i) Imputed amount for out-of-pocket expenditures for medical services from MEPS (statistical match)
    ii) Imputed family share of health insurance premiums from CE (using a statistical match)
5) SIPP Predictive Mean
    i) Imputed amount for out-of-pocket expenditures for medical services from MEPS (predictive mean match)
    ii) Imputed family share of health insurance premiums from CE (using a statistical match)

V. Results

Table 1, Table 2 and Table 3 give the results of this analysis. Table 1 shows the average dollar amount for family MOOP. For this table, the family is defined as the family unit for December 1996. Table 2 and 3 shows how poverty rates differ when the different imputations are used. Table 3 further shows how increases in the poverty rate differ from each other. For this table, the family structure is allowed to change monthly because poverty rates concern individuals, not families.

The effects between the imputations are presented in the tables. The list of sub-categories analyzed are sex, race/ethnicity, marital status of the family, headship of the family, insurance status, family labor force attachment, work limitations, disability days and self-reported health status. However, the discussion is limited to the sub-categories where the imputation models have strong disagreements.

Table 1 reveals that across most categories there are distinctive trends in the imputed values. The Doyle match and the Predictive Mean match, on average, imputes the lowest amount of family MOOP, the "reported" family MOOP amount from MEPS is the third lowest, and the "reported" amount from SIPP and the Betson model tends to produce the higher average amounts for family MOOP.

The method of statistical matching causes the donor and recipient files to be similar. This is roughly the case when comparing the Doyle statistical match and the Predictive Mean match and the MEPS "reported" amount. The largest inconsistency between the Doyle match and the MEPS "reported" amount is for the elderly; the MEPS MOOP is much larger than the Doyle MOOP is for the elderly. Within the third panel for alternative poor families, another difference arises. The Doyle match assigned more MOOP to families that had at least one full-time full-year worker and less to families that had no labor force attachment during the year when compared to MEPS. The Predictive Mean match was pretty close to the MEPS "reported" amount for both the elderly and family employment status.

Compared to MEPS, the Betson model assigned more MOOP to families that had no labor force attachment during the year and less MOOP to families that had at least one adult working full-time full-year. Otherwise, the Betson imputation typically gave a higher value for family MOOP than MEPS would indicate.

The "reported" amount from SIPP was similar to the "reported" amount from MEPS for the first panel of all families and the second panel of poor families. However, using our alternative definition of poor (panel 3), the "reported" amount has much higher MOOP values than all other imputations in most subcategories.

These trends in the average dollar amount of family MOOP can be deceiving. The percent of the families reporting family MOOP is going to affect the average family MOOP amounts. The goal of MEPS is to collect medical utilization information. As a result, MEPS successfully collects small and large amounts of out-of-pocket expenditures from medical utilization. Virtually every family in MEPS reported some MOOP, even when it was small. Large amounts of MOOP are more likely to be remembered than the smaller amounts unless the respondent is sufficiently probed with questions. These small amounts of family MOOP lower the average dollar amount. Therefore, the results in Table 1 have to be viewed with caution because of the different reporting rates of MOOP.

Comparing alternative poverty rates provides a better method of comparing the imputations of MOOP. If 30% of near poor families had small amounts of MOOP, but did not report it in SIPP, there should only be a small *additional* impact on alternative poverty rates. If this is the case, then the "reported" amounts of MOOP in SIPP might be good enough for the purposes of alternative poverty rates even though they are high when compared to the other average MOOP amounts.

Table 2 shows how the distribution of poverty changes when our alternative poverty rate is applied. Each subcategory equals 100%. Although the underlying poverty rate must go up by subtracting MOOP from family income, the distributional effect on poverty may follow different patterns. In all imputations the poverty shifts away from the young and towards the elderly. In the family employment category, most of the imputations indicate that poverty shifts towards families with full-time full-year workers and away from families with no labor force attachment.

Table 3 shows both the poverty rates and the growth in poverty when using our alternative poverty rate. As expected, the poverty rate in MEPS is higher than the poverty rate in SIPP.

The first panel of Table 3 compares the official poverty rate from MEPS and the alternative poverty rate of MEPS. The same comparison is made with the official SIPP poverty rates and the alternative SIPP poverty rates. There is no significance testing because subtracting MOOP (or anything else) from family resources is always going to be a significant change for the family. Instead, the comparison is one of magnitude (a fifteen percent increase in poverty).

For MEPS and the SIPP imputations, large changes occur in the poverty rate for the elderly. In the family employment category, the MEPS "reported", SIPP "reported", the Doyle and the Predictive Mean match have alternative poverty rates that are large changes for families that have at least one full-time full-year working adult.

Panel one of Table 3 also has results that are not in agreement with the general trends. The poverty rate using the Betson imputation caused large increases for families that had no labor force participation over the entire year. The "reported" SIPP amount and the Predictive Mean match for middle-aged adults caused a large increase in the poverty rate whereas MEPS and the other imputations did not.

When comparing the poverty rates from the Betson model and the Doyle match, a few differences are apparent. The Doyle match has higher poverty rates for the non-elderly and lower poverty rates for the elderly when compared to the Betson model. Similarly, the Doyle match has a higher alternative poverty rate for families with full-time full-year workers and a lower poverty rate for families with no labor force attachment when compared to the Betson model.

The second panel of Table 3 shows the percentage increase in poverty when using our alternative definition of poverty. SIPP growth rates are compared to the growth rate in MEPS. Significance tests and magnitude are the focus of this part of the table. Using growth rates mitigates the influence of the different levels of poverty across MEPS and SIPP.

In the second panel, the usual view of significance testing is not followed. The best results are insignificant results. Insignificance between the MEPS and SIPP growth rates indicate that MOOP in SIPP causes the same growth in poverty as does MEPS. SIPP results that are extremely different from the MEPS growth rate and are significant are denoted with an α. SIPP growth rates that are significantly different from the MEPS growth rate, but are not very large in magnitude, fall in-between the ideal result (no significance) and the worst result (significance, large magnitude change). The following discussion focuses on deviations from the MEPS growth rates in poverty categories. The focus of the discussion will continue to center on a few variables.

Overall, the results from the second panel of Table 3 are mixed. The Betson model is the only imputation to produce an overall increase in poverty that is not statistically different from MEPS. However, almost all of the subcategories are significantly different and large in magnitude. Children, middle-aged people and families with at least one adult that worked full-time full-year have comparatively low growth rates whereas the elderly and families with no labor force attachment have much higher growth rates than MEPS would indicate. The Betson model does not do well compared to MEPS, by this standard. Along these same categories, the Predictive Mean match performs equally poorly.

The Doyle match is significantly different for adults between the ages of 18 and 45. The growth in family MOOP is much higher for families with a full-time full-year worker and the families that have some labor force participation.

The growth in poverty using the "reported" SIPP amount was significantly larger for middle aged adults and much larger for adults age 65 to 74 than MEPS would indicate. It also had a much larger increase in the poverty rate for families with at least one full-time all-year worker.

VI. Conclusion

This paper has shown that MOOP has the potential make people impoverished. Consistently the results show that many subcategories of people become poor if MOOP is accounted for. In particular, the imputations consistently show that some subgroups are more likely to feel the impact of poverty than others. The elderly and white nonHispanics consistently have large increases in their poverty rates. Some of the other subcategories have basic agreement that the burden of MOOP impoverishes many families. For instance, families with a married couple or that do not have a female head, families that have at least one full-time, full-year worker, workers with more that five sick days or people in fair to poor health are particularly susceptible to the impoverishing affect of MOOP.

The results presented are consistent with Doyle (1997b). In Doyle's previous paper, using the National Medical Expenditure Survey, the primary disagreement between the statistical match and Betson's model was along age and family employment status. This result has been replicated using SIPP data. We believe that the results from the Betson's model differs from the Doyle match because the Betson model treats health insurance differently and treats the elderly as a separate unit from the rest of the family. These modeling assumptions are not a part of the Doyle match. The Doyle match primarily focuses on individual characteristics in determining the MOOP value for people in SIPP. For most of the subcategories, this paper would suggest that using the Doyle method for statistical matching is an improvement over a model-based approach.

The impact from subtracting the "reported" MOOP from SIPP was surprisingly accurate at mimicking the growth rate of poverty when compared to MEPS. As was argued previously, this might indicate that the smaller amounts of MOOP that are unobserved in SIPP make small differences in alternative poverty rates. However, obtaining values for small MOOP amounts may be important independent of alternative poverty rates.

Because the statistical match performed about as well as the "reported" SIPP amount and the Predictive Mean match, and slightly better than the Betson model, the approach of using a statistical match has been validated.

Overall, the imputation strategies were successful. Each MOOP amount contained an element of imputation with reasonable results.

VII. Future Research

The Betson model may have higher values for MOOP and alternative poverty rates because it was estimated on the CE and not MEPS. We would guess that rerunning the Betson model on MEPS would produce results much closer to the MEPS in the above comparisons leading to lower values of imputed MOOP and a larger number of families having MOOP. Due to Betson's modeling assumptions, we would expect the same differences to occur. This should be investigated when MEPS provides a complete MOOP value for all individuals in the survey.

The success of the statistical match in this scenario of imputing MOOP indicates that it should be successful in developing a MCRI measure. A future MCRI measure could be added to the Medical Expenses and Utilization of Health Care Topical Module with a secondary value for MOOP.

VIII. References

Armstrong, J. "An Evaluation of Statistical Matching Methods" Working Paper No BSMD-90-003: Methodology Branch, Direction De Methodologie.

Banthin, Jessica "Imputing Premiums in the MEPS: Making a silk Perse out of a Sows Ear." AHRQ presentation, 2001

Bavier, Richard "Do the current poverty thresholds include any amount for health care?" Washington, DC: U.S. Department of Commerce, Bureau of the Census, 2001.

Betson, David "Imputation of Medical Out-Of-Pocket (MOOP) Spending to CPS Records." Washington, DC: U.S. Department of Commerce, Bureau of the Census, 2001.

Campbell, Jennifer and Pat Doyle. "Medical Out-Of-Pocket Expenditures and Alternate Poverty Measures: A First Step." Conference Proceedings, ASA, 2000.

Citro, Constance F. and Robert T. Michael, Editors. *Measuring Poverty: A New Approach*. Washington, DC: National Academy Press, 1995.

Doyle, Pat "Who's at Risk? Designing a Medical Care Risk Index" Washington, DC: U.S. Department of Commerce, Bureau of the Census, May 1997a.

Doyle, Pat A. "How Do We Deduct Something We Do Not Collect? The Case of Out-Of-Pocket Expenditures" Washington, DC: U.S. Department of Commerce, Bureau of the Census, August 1997b.

Federal Committee on Statistical Methods. "Report on Exact and Statistical Matching Techniques." Statistical Policy Working Papers. Washington, DC: US Office of Management and Budget, 1980.

Naifeh, Mary. "Trap Door? Revolving Door? or Both?: Dynamics of Economic Well-Being 1993-1994", U.S. Government Printing Office, Washington, DC, 1997.

Short, Pamela Farley and Jessica S. Banthin "New Estimates of the Underinsured Younger than 65 Years" Journal of the American Medical Association, October 25, 1995, Vol 274, No. 16, pp 1302-1306.

Sullivan, Teresa, A., Elizabeth Warren, Jay Lawrence Westbrook. *The Fragile Middle Class: Americans in Debt*. Yale Press, 2001.

Table 1: Average Family MOOP by Category, 1996

	All Families					Poor Families (official rate)					Poor Families (alternative rate)				
	MEPS	SIPP				MEPS	SIPP				MEPS	SIPP			
	"R"	"R"	B	D	PM	"R"	"R"	B	D	PM	"R"	"R"	B	D	PM
Averg. MOOP for Family	$1,697	$1,630	$2,017	$1,459	$1,595	$754	$911	$918	$704	$644	$1,016	$1,727	$1,333	$951	$931
By Age															
Less than 18	1,618	1,460	1,861	1,480	1,540	660	681	757	688	576	838	1,142	892	884	712
Adults age 18 to 44	1,458	1,462	1,724	1,381	1,438	609	899	734	643	567	807	1,597	1,001	922	774
Adults age 45 to 64	1,868	1,921	2,208	1,594	1,803	1,032	1,485	682	878	882	1,333	2,677	1,161	1,119	1,261
Adults age 65 to 74	2,317	2,050	2,736	1,438	1,903	1,199	1,289	1,635	778	881	1,745	3,161	2,256	1,155	1,796
Adults age 75+	2,384	1,995	2,931	1,422	1,803	1,317	1,385	2,106	773	955	1,853	2,829	2,861	1,030	1,651
By Sex															
Male	1,707	1,630	2,023	1,467	1,600	767	942	869	717	636	1,046	1,778	1,291	1,024	951
Female	1,687	1,631	2,011	1,453	1,591	746	889	951	694	650	994	1,690	1,362	899	917
By Race/Ethnicity															
Hispanic	1,185	1,184	1,759	1,182	1,084	501	712	864	588	421	711	1,126	1,018	1,072	627
Black nonHispanic	1,059	1,174	1,795	1,093	1,043	498	673	893	531	487	564	1,077	1,217	643	579
White nonHispanic	1,881	1,748	2,085	1,559	1,752	999	1,125	974	850	825	1,365	2,250	1,555	1,063	1,238
Other nonHispanic	1,519	1,539	1,939	1,396	1,662	646	645	799	753	789	702	1,084	1,147	852	941
By Type of Family (Marital Status/Head)															
Single	2,004	1,833	2,224	1,678	1,855	1,059	1,190	906	916	844	1,480	2,468	1,540	1,336	1,331
Married Couple	1,032	1,119	1,540	967	1,014	531	747	922	591	535	644	1,232	1,245	728	692
Male Head or Joint	1,880	1,719	2,120	1,562	1,726	992	1,170	893	772	727	1,421	2,309	1,414	1,189	1,138
Female Head	1,384	1,500	1,865	1,316	1,414	599	779	929	668	602	733	1,394	1,292	818	816
By Insurance Status															
Insured All Year	1,854	1,692	2,119	1,569	1,733	804	921	1,032	789	697	1,116	1,829	1,556	990	1,068
Insured Part Year	1,241	1,455	1,730	1,021	1,114	769	908	783	563	562	925	1,686	1,054	752	709
Uninsured	1,057	1,160	1,275	963	905	606	882	723	597	577	806	1,396	890	1,088	733
By Employment Status of the Family															
Worked full-time all-year	1,752	1,610	2,011	1,575	1,702	830	916	673	808	730	1,169	2,155	1,227	1,404	1,111
Unemployed all-year	1,775	1,765	2,277	1,195	1,432	821	924	1,105	679	648	1,058	1,667	1,597	801	979
Other	981	1,614	1,762	1,129	1,216	530	895	823	662	581	668	1,440	1,025	781	737
By Work Limitations															
None	1,667	1,594	2,018	1,458	1,590	714	851	939	677	612	962	1,650	1,355	945	904
Limited in Work	2,116	2,137	2,111	1,511	1,710	875	1,231	756	801	794	1,328	2,245	1,226	913	1,003
Prevented from Work	2,098	2,089	1,923	1,459	1,640	1,146	1,343	788	867	845	1,441	2,234	1,184	1,005	1,110
By Disability Days															
None	1,677	1,524	2,025	1,399	1,531	697	778	896	646	579	942	1,401	1,289	866	846
1 to 5	1,600	1,614	1,965	1,562	1,682	738	946	898	758	704	980	1,781	1,311	1,097	977
6 to 10	1,762	2,003	2,027	1,634	1,699	990	1,086	1,094	859	713	1,332	2,373	1,614	1,358	974
11+	2,036	2,580	2,150	1,574	1,884	1,045	1,785	1,029	955	1,004	1,396	3,515	1,548	1,078	1,448
By Self-Reported Health Status															
Excellent	1,759	1,502	1,938	1,431	1,568	760	798	798	665	558	1,029	1,267	1,023	891	769
Very Good	1,650	1,542	1,976	1,474	1,563	705	838	830	666	595	974	1,602	1,227	956	831
Good	1,610	1,676	2,087	1,454	1,600	677	794	898	674	608	899	1,687	1,347	887	899
Fair	1,801	2,012	2,236	1,532	1,707	838	1,226	1,167	784	791	1,081	2,208	1,706	1,102	1,158
Poor	2,192	2,513	2,216	1,470	1,839	1,124	1,428	1,180	916	971	1,525	2,802	1,727	1,062	1,440
% of families with MOOP	94.3%	75.0%	64.9%	95.0%	95.6%	85.4%	51.7%	64.9%	86.9%	88.7%	94.3%	56.9%	69.8%	88.5%	90.2%
Total number of families in universe (in millions)	119.9	113.3	113.3	113.3	113.3	19.1	14.8	14.8	14.8	14.8	21.3	16.6	17.2	16.8	17.1

"R" stands for the results that used the reported value with the necessary imputation. B stands for results uing the Betson model. D stands for the results using the Doyle match. PM stands for results using a predictive mean match.

1. 1) if at least one adult family member works full-time throughout 1996. 2) If the family has no labor force attachment (unemployed).
3) If the family has some labor force attachment (other)

TABLE 2: Distribution of Poor Persons by Category, 1996

	MEPS		SIPP				
	Official	"R"	*Official*	"R"	B	D	PM
# of Persons in Poverty (mill)	39.9	44.3	32.8	36.8	36.5	36.8	37.3
By Age							
Less than 18	37.7%	36.5%	42.0%	39.9%	39.1%	40.5%	39.8%
Adults age 18 to 44	39.1	38.2	35.9	34.9	34.4	35.4	35.0
Adults age 45 to 64	13.5	13.5	12.2	13.0	11.7	14.5	12.7
Adults age 65 to 74	5.1	6.0	4.8	5.8	6.7	5.6	6.0
Adults age 75+	4.6	5.8	5.1	6.4	8.1	6.1	6.5
By Sex							
Male	43.2	43.3	42.5	42.6	42.0	42.6	42.6
Female	56.8	56.8	57.4	57.4	58.1	57.4	57.4
By Race/Ethnicity							
Hispanic	23.4	22.5	23.3	21.9	22.0	22.7	22.4
Black nonHispanic	24.5	23.3	26.3	24.9	25.4	25.2	24.7
White nonHispanic	47.4	49.5	45.3	48.4	47.6	47.0	47.9
Other nonHispanic	4.7	4.8	5.2	5.0	5.0	5.1	5.0
By Type of Family (Marital Status/Head)							
Single	60.6	58.3	66.2	63.6	66.1	64.4	64.1
Married Couple	39.4	41.7	33.8	36.4	33.9	35.7	35.9
Male Head	39.4	40.8	34.9	36.6	35.3	36.2	36.3
Female Head	60.6	59.2	65.1	63.4	64.7	63.8	63.7
By Insurance Status							
Insured All Year	57.8	59.2	58.5	59.8	60.4	59.5	60.0
Insured Part Year	19.5	19.1	23.4	22.9	22.4	23.0	22.8
Uninsured	22.7	21.7	18.1	17.3	17.2	17.6	17.2
By Employment Status of the Family[4]							
Worked full-time all-year	40.0	41.6	24.1	26.0	24.0	26.0	25.7
Unemployed all-year	35.5	35.0	39.7	39.1	41.5	38.9	39.5
Other	24.5	23.4	36.3	34.9	34.5	35.1	34.8
By Work Limitations (Adults)							
None	88.6	88.3	85.5	85.5	85.7	85.5	85.4
Limited in Work	4.2	4.5	3.3	3.4	3.2	3.2	3.2
Prevented from Work	7.3	7.3	11.2	11.1	11.1	11.2	11.3
By Disability Days							
None	73.1	72.5	70.1	68.7	69.3	69.2	69.3
1 to 5	11.9	12.3	16.9	17.1	16.9	17.2	17.0
6 to 10	4.1	4.2	4.4	4.7	4.5	4.6	4.5
11+	11.0	11.0	8.7	9.6	9.2	9.0	9.1
By Self-Reported Health Status							
Excellent	15.8	16.1	26.6	25.6	25.4	26.0	25.8
Very Good	30.9	30.8	26.3	25.8	25.8	25.9	25.7
Good	31.9	31.5	26.6	26.7	26.5	26.5	26.6
Fair	14.8	14.8	13.0	13.8	14.1	13.9	13.8
Poor	6.5	6.9	7.5	8.1	8.2	7.7	8.1

Italics indicates it is the comparison group.
(Panel 1): **Bold/*** indicates the difference between the comparision group is greater than 15%.
(Panel 2): ^ indicates significance at the 95% level.
(Panel 2): **Bold/α** indicates that the difference is greater than 30% and significant.
"R" stands for the results that used the reported value with the necessary imputation. B stands for results using the Betson model. D stands for the results using the Doyle match. PM stands for results using a predictive mean match.

1. 1) If at least one adult family member works full-time throughout 1996.
2) If the family has no labor force attachment (unemployed).
3) If the family has some labor force attachment (other)

Source: U.S. Census Bureau, 1996 SIPP AHRQ, 1996 MEPS BLS, 1996 CE

Table 3: Official versus Alternative Poverty Rates, 1996

	Comparing the Official and Alternative Poverty Rates							**% Increase in Poverty**					
	MEPS		SIPP					MEPS	SIPP				
	Official	"R"	*Official*	"R"	B	D	PM	***"R"***	"R"	B	D	PM	
Poverty Rates	*14.9%*	16.5%	*12.3%*	13.8%	13.7%	13.8%	**14.2%***	*10.9%*	12.3%^	11.4%	12.3%^	**15.3%**$^{\alpha}$	**% Change**
By Age													
Less than 18	*21.6*	23.2	*19.0*	20.3	19.7	20.5	20.5	*7.5*	6.7	**3.5**$^{\alpha}$	8.1	7.7	
Adults age 18 to 44	*14.1*	15.4	*11.2*	12.3	12.0	12.4	12.4	*8.6*	9.4	6.8^	10.7^	10.9^	
Adults age 45 to 64	*9.8*	10.8	*7.2*	**8.6***	7.7	8.3	**8.6***	*11.0*	**19.2**$^{\alpha}$	**6.5**$^{\alpha}$	14.2^	**18.4**$^{\alpha}$	
Adults age 65 to 74	*10.9*	**14.2***	*8.3*	**11.3***	**13.0***	**11.0***	**11.9***	*30.3*	35.5^	**56.2**$^{\alpha}$	31.9	**42.2**$^{\alpha}$	
Adults age 75+	*13.2*	**18.3***	*11.6*	**16.4***	**20.6***	**15.6***	**16.9***	*38.6*	41.2	**77.7**$^{\alpha}$	34.6	45.6^	
By Sex													
Male	*13.2*	14.7	*10.8*	12.1	11.8	12.1	12.2	*11.1*	12.3	9.7	12.3	13.6^	
Female	*16.5*	18.3	*13.8*	15.5	15.5	15.5	15.7	*10.8*	12.2^	12.6^	12.2^	13.8^	
By Race/Ethnicity													
Hispanic	*31.8*	33.8	*26.5*	28.0	28.0	29.1	29.1	*6.5*	5.7	5.5	**9.7**$^{\alpha}$	**9.7**$^{\alpha}$	
Black nonHispanic	*29.7*	31.3	*27.2*	28.8	29.3	29.2	29.0	*5.5*	6.0	7.8	7.5	6.8	
White nonHispanic	*9.8*	**11.3***	*7.6*	**9.2***	**8.9***	**8.9***	**9.2***	*15.8*	19.8^	16.9^	16.5	20.2^	
Other nonHispanic	*16.6*	18.6	*15.3*	16.4	16.3	16.9	16.8	*12.0*	7.6	7.1	10.6	10.2	
By Type of Family (Marital Status/Head)													
Single	*27.2*	29.0	*25.4*	27.4	28.3	27.7	28.0	*6.8*	7.8	**11.2**$^{\alpha}$	**9.0**$^{\alpha}$	**10.1**$^{\alpha}$	
Married Couple	*8.8*	**10.3***	*6.1*	**7.4***	6.9	**7.3***	**7.4***	*17.3*	21.0^	**11.7**$^{\alpha}$	18.4^	20.9^	
Male Head	*9.4*	10.8	*7.4*	**8.7***	8.3	**8.6***	**8.7***	*14.8*	17.9^	12.6^	16.4^	18.3^	
Female Head	*24.2*	26.2	*19.2*	21.0	21.3	21.1	21.4	*8.4*	9.3	10.7^	10.0	**11.3**$^{\alpha}$	
By Insurance Status													
Insured All Year	*11.3*	12.8	*9.1*	10.4	10.4	10.4	**10.6***	*13.6*	14.9^	14.9^	14.1	16.6^	
Insured Part Year	*24.8*	**30.0***	*23.7*	26.0	25.2	26.1	26.2	*20.7*	**9.9**$^{\alpha}$	**6.7**$^{\alpha}$	**10.2**$^{\alpha}$	**10.7**$^{\alpha}$	
Uninsured	*28.2*	29.9	*26.7*	28.6	28.3	29.1	28.9	*6.2*	7.1	5.9	8.9	8.3	
By Employment Status of the Family[1]													
Worked full-time all-year	*7.6*	**8.8***	*4.2*	**5.0***	4.6	**5.0***	**5.1***	*15.6*	**20.9**$^{\alpha}$	11.0^	**20.9**$^{\alpha}$	**21.3**$^{\alpha}$	
Unemployed all-year	*38.7*	42.3	*34.2*	37.9	**39.9***	37.7	38.8	*9.2*	10.9	**16.5**$^{\alpha}$	10.2	**13.4**$^{\alpha}$	
Other	*45.3*	47.9	*30.8*	33.3	32.7	33.5	33.6	*5.8*	8.1	5.9	**8.7**$^{\alpha}$	**9.0**$^{\alpha}$	
By Work Limitations (Adults)													
None	*14.2*	15.7	*11.4*	12.8	12.7	12.8	12.9	*10.7*	12.3^	11.7^	12.3^	13.7^	
Limited in Work	*18.2*	**21.6***	*13.8*	**16.1***	14.7	15.1	15.3	*18.7*	16.7	**6.7**$^{\alpha}$	**9.5**$^{\alpha}$	**11.2**$^{\alpha}$	
Prevented from Work	*32.0*	35.3	*30.8*	34.2	34.0	34.6	**35.5***	*10.3*	11.0	10.5	12.6	15.2	
By Disability Days													
None	*14.9*	16.5	*13.1*	14.5	14.5	14.6	14.8	*10.1*	10.1	10.2	10.9	12.5^	
1 to 5	*12.1*	13.9	*8.6*	9.8	9.6	9.8	**9.9***	*14.9*	13.6	12.0^	14.2	15.0	
6 to 10	*13.0*	**15.0***	*12.1*	**14.7***	13.9	**14.5***	**14.3***	*15.1*	**21.1**$^{\alpha}$	14.3	19.1	17.8	
11+	*21.0*	23.3	*18.8*	**23.1***	**22.2***	**21.8***	**22.4***	*10.8*	**22.9**$^{\alpha}$	**17.9**$^{\alpha}$	**15.8**$^{\alpha}$	**18.9**$^{\alpha}$	
By Self-Reported Health Status													
Excellent	*9.8*	11.0	*9.4*	10.2	10.0	10.3	10.4	*12.4*	**8.2**$^{\alpha}$	**6.1**$^{\alpha}$	9.4^	10.1^	
Very Good	*12.2*	13.5	*10.5*	11.6	11.5	11.7	11.7	*10.4*	10.1	9.2	10.7	11.1	
Good	*18.3*	20.1	*14.6*	16.4	16.2	16.3	16.6	*9.8*	**12.8**$^{\alpha}$	11.3	12.2^	**14.1**$^{\alpha}$	
Fair	*24.4*	26.9	*19.2*	**22.8***	**23.2***	**23.0***	**23.1***	*10.4*	**18.9**$^{\alpha}$	**20.6**$^{\alpha}$	**19.8**$^{\alpha}$	**20.2**$^{\alpha}$	
Poor	*32.1*	**37.5***	*25.3*	**30.9***	**30.8***	29.1	**31.4***	*16.8*	22.0	21.8	14.9	**23.9**$^{\alpha}$	

Italics indicates it is the comparison group.

(Panel 1): **Bold/*** indicates the difference between the comparision group is greater than 15%.

(Panel 2): ^ indicates significance at the 95% level. **Bold/**α indicates that the difference is greater than 30% and significant.

"R" stands for the results that used the reported value with the necessary imputation. B stands for results using the Betson model. D stands for the results using the Doyle match. PM stands for results using a predictive mean match.

1. 1) if at least one adult family member works full-time throughout 1996. 2) If the family has no labor force attachment (unemployed). 3) If the family has some labor force attachment (other)

Source: U.S. Census Bureau, 1996 SIPP AHRQ, 1996 MEPS BLS, 1996 CE

APPENDIX

A. THE STATISTICAL MATCHING SOFTWARE

The process of matching is finding individuals with similar characteristics in two separate data sources. In one data source (the donor file), there is important information that the primary data source does not contain (the recipient file). When similar persons are found, the donor file donates the information that the recipient file did not have to each record considered a "match".

Suppose a good match occurred in the following manner. The researcher believes that a person with disabilities always needs to be matched to a person with disabilities. If not, the match is unacceptable. In this example, all persons are divided into two groups, persons with and without disabilities. Essentially, this example **partitions** the data source into two parts; this is referred to as "**blocking**" variables.

In the second stage of picking a good match, variables are selected that are important in determining the variable to be carried over (e.g. MOOP). For instance, we might not believe the exact number of visits to the dentist is important. However, the best match would still be when the donor file has a person with disabilities who has gone to the dentist the same number of times as in the recipient file. If this did not happen, then a person would be selected who had disabilities and a similar number of dental visits (± one visit is better than ± two visits). The same logic applies to the other group (the other partition), persons without disabilities.

Formally, this technique is a multivariate **nearest neighbor** match; some variables have a zero distance (the values of the variables must be the same – the blocking variables) while other variables are matched according to non-zero distance measures (the variables could have different values). A perfect match, when the values for all variables are identical, has a distance of zero. As the values become farther apart, as in the dental visit example, the distance measure has a higher value. The best match is the match with the smallest distance.

Heacock's "Generalized Statistical Match" software (GSM) was used for statistical matching. His software uses a two-stage design for statistical matches that follow the logic above. In the first stage, the researcher selects variables that are deemed the most essential for the match; these are the blocking variables that partition the data (disability in the example above). To have a match at all, the values of these variables must be identical.[3] In other words, this first stage clusters the potential donors into groups. The selection process of which potential donor to use is controlled by the second stage of his software.

The second stage introduces and structures the randomness involved in this matching process. Without the second stage, a simple random match (with replacement) would be made from the pool of possible donors (the cluster defined in stage one). Second stage variables do not need to have exactly the same value (in the donor and recipient files) for a person to be considered a good match. These second stage variables can be weighted. If a variable is considered more important than another is, then it can be given a greater weight. For example, if the data user believes that going to the dentist is ten times more important then being married to achieve a good match, then the dentist variable would receive a weight of 10 and married would get a weight of 1. A higher weight produces a higher penalty for being different from potential donors.

[3] If the cell size is to small to get an identical match, the cell can be collapsed.

The second stage results in the final match between the data sources. At this stage, variables are introduced that are important, but it is not crucial that they match. By adding up the distances[4] between the variables, the program selects the observation that has the smallest distance and pulls the borrowed value from the donor data source.

This approach has the drawback of lacking statistical properties and has a sense of arbitrariness in the weighting of second round variables. However, it was found to more closely represent the donor file's distribution when it is difficult to predict the variable that is borrowed.

Before the software can be used, the **two data files** need to be transformed into similar products. To use a variable in the matching process, it must exist in each file. These variables were either part of the initial file or were created so that a given variable was comparable on both data sources. For instance, education was measured the same while occupational codes needed to be made consistent across data sources. The only difference between the donor file and the recipient file is that the donor file has the variable that is being donated (MOOP less out-of-pocket costs from health insurance premiums); otherwise, the two files have exactly the same information. Both files have normalized weights to help replicate the distribution of the donated variable onto the recipient file.

B. THE IMPUTATION MODELS

The procedures described here are for the imputation techniques. They apply to the out-of-pocket costs related to medical services, except where noted. New poverty rates are calculated for each imputation. In the model and the matches, each individual recieves an imputed value for premiums and out-of-pocket expenses from medical services. This amount is then summed up to the family level. This family level MOOP is assigned to each family

[4] Distance can be defined four ways in this program: any difference, absolute difference, percentage difference (percent disagreement) and a combination of absolute and percentage differences.

member. Resources were computed as total family income minus the family amount for the imputed moop. Poverty status was computed as resources divided by the official poverty threshold for a given size family[5].

For out-of-pocket costs from health insurance premiums, as already noted, the imputation approach was always used the method of the Doyle (1997b) match. This will be discussed below.

B.1 Betson (2001) Imputation Model

Betson's model uses a unique approach to impute MOOP. We briefly outline his approach here. He takes the 1996-1997 CE data as the basis for his imputation. Initially, the population is divided into 40 categories based on family characteristics. If the head of the family is under 65 years of age, the family is categorized into one of thirty-two categories based on insurance status, age, family size and near-poverty status. For family heads that are 65 years old or older, the families are broken down into eight categories based on age, family size and near-poverty status.

[5] There is a running debate on whether or not the poverty thresholds already include medical expenses. See Bavier (2001). This paper does not address this debate. The focus is on marginal effects of different imputation techniques.

Within each category, he determines the percent of families that report zero MOOP (ρ_i). After recording this number for each of the forty categories, he deletes the families without MOOP. Within each category, all of the families have their MOOP ranked from low to high creating a cumulative density function. This ranking is assumed (and looks like it is) to fit a log-logistic function. He uses the log(CDF (1-CDF)) and regresses a constant, and a cubic power funtion of log-MOOP to fit that curve. Once the CDF and the beta's are known for a given group, the information can be carried over to the primary dataset. His equation is below.

1) $\text{LOGODDSRATIO}=B_0 + B_1*\text{Log(MOOP)} + B_2*\text{Log(MOOP)}^2 + B_3*\text{Log(MOOP)}^3$

On the primary dataset, families were gathered into the same 40 categories that were used in the CE dataset. Each family was also assigned two random numbers and their relevant beta coefficients. The first random number determined the amount of MOOP the family was assigned. Let's assume that the original equation was only log(CDF (1-CDF)) regressed on a constant and log-MOOP. If the random number was 0.2 then the assigned amount of log-MOOP roughly corresponded to the 20th percentile on the distribution of the CDF. Once the log-MOOP is solved for MOOP, that value becomes the family's potential value for MOOP. This explanation is overly simplified because the log-logistic function of a power series is not as intuitive. Once a value was assigned to each family, the second random number becomes important. If the random number (0 to 1) is greater than the proportion of families that do not have MOOP (ρ_i), then the assigned MOOP value is used. If the random number is less than or equal to ρ_i then the family is assigned zero MOOP.

B.3 "Nearest Neighbor" Matches

Matching is a technique for imputing the value of a variable from one dataset to another. This can be done when relevant variables are contained in both datasets. In the case of out-of-pocket expenses for medical services, having variables that deal with utilizing medical services are relevant variables that could potentially allow for a good match. A good review of the statistical matching literature is by Armstrong (1989) or the Federal Committee on Statistical Methods (1980).

For each statistical match, MOOP was imputed to individuals and then summed up to the family level.

B.31 Predictive Mean

The **predictive mean** approach is a regression-based match. As with all imputation techniques, the same variables must be on both data sources. A regression, using the same variables used in the other statistical matches, was run on the donor data source. Using the regression coefficients, a predicted value for MOOP[6] was calculated for both the donor and recipient file. For a simple predictive mean, the donor and recipient file could be matched on the predicted value for MOOP (the predicted value for the donor variable is the blocking variable). A more complex method would be to include other variables after the group matches are made. Including variables in the distance function can do this. In other words, within a match on MOOP, all of the common variables can be included to make a closer match. An even better match could be made if cross-effects were used.

In this paper a more "complex" approach were used. In a simple approach, persons would be matched if they had the same predicted MOOP. In the complex approach used,

[6] Actually, the natural log of MOOP, rounded to the first decimal, was used to do this match.

persons were 1) first matched on predicted MOOP and then 2) matched by the exogenous variables, using the Fisher's z-transformation of the regression coefficients for weights. The equation is below is for the log of out-of-pocket expenditures due to medical services. The R2=.32.

Variable	beta	z	std error
constant	6.482	-	0.075
age	0.017	0.232705	0.001
male	-0.229	-0.069302	0.034
fdisab	0.057	0.01209	0.053
evisdoc	0.006	0.09889	0.001
edaysick	0.002	0.02373	0.001
daydrug	1.720	0.436715	0.046
fsize	-0.095	-0.092594	0.013
povr	0.060	0.10338	0.007
hosp1	0.626	0.09498	0.071
pov100	-0.745	-0.154949	0.061
hgood	0.063	0.013654	0.057
ins2	0.115	0.021185	0.058
ins3	0.681	0.12589	0.061
race1	-0.579	-0.132571	0.062
race2	-0.823	-0.158394	0.057

Regression from MEPS with Z weights (*100) as the basis for advanced match.

The following is are what the variables represent:
1) *age* is in years. 2) *evisdoc* is the number of visits to the doctor. 3) *edaysick* is the number of days that the person stayed in bed for at least half of the day. 4) *daydrug* is whether the person takes medication on a daily basis 5) *fsize* is family size 6) *povr* is the poverty ratio 7) *hosp1* is whether the person spent one or more days in the hospital 8) *pov100* is whether the person fell below the poverty line 9) *hgood* is whether the persons health was good or excellent 10) *ins2* is whether the person had insurance for only part of the year 11) *ins3* is whether the person was uninsured the whole year 12) *race1* is whether the person was of hispanic ethnicity 13) *race2* is whether the person was Black nonHispanic.

B.32 Doyle (1997b) Recommendation

Doyle (1997b) concluded that, based on her experience with NMES, the best approach for obtaining information useful for producing a high quality value for MOOP and a medical risk care index (MCRI) was a statistical match. In that paper, MOOP was matched to give insight into alternative poverty measures. Doyle's approach was to make an initial match (the blocking/partitioning step) using the following variables: disability, insurance status, one or more hospital vistits, health status and family size. For the final match (the distance measures), the variables used included: utilization of dental, physician service, or drug use, bed days, age, race, poverty status, and sex. The person most closely resembling the combination of second step variables, was chosen as the match. Unlike Doyle's paper, the current version of the **GSM** Software does not have a method for breaking ties. Medical utilization variables were given a weight of 10 and the other variables were given a weight of 8.

This type of match was conducted ten separate times with a different seed for the random number generator. The range for the overall alternative poverty rate using this method was from 13.67% and 13.73%. The average value was 13.71%. In the tables, the trial that was closest to the average poverty rate was used.

B4 Health Insurance Premiums from CE

As discussed in the text, the imputation of premiums to both MEPS and SIPP was necessary because MEPS did not collect, for the majority of families, any health insurance premium data. Doyle's (1997b) approach was used because it performs well in the absence of relevant exogenous variables; predicting how much an employee must spend on health insurance probably depends on idiosycratic employer characteristics.[7]

[7] When we tried a regression based approach, an R^2=.04 was obtained. To use a predictive mean match, a reasonable regression model is necessary.

The Doyle (1997b) method includes blocking/partitioning the observations and within the partitioned group choosing a particular donor based on distance measures. A predictive mean approach was inappropriate due to the lack of variables that could predict how much a persons premiums were given a type of plan (employer-sponsored-family-paid for in part, employer-sponsored-family-where the employer paid none, etc).

The limited information of privately purchased health insurance from MEPS was not used because 1) AHRQ warns that this data has problems with widespread non-response and 2) we did not want to impute some, but not all, of the privately purchased insurance premiums. Therefore the decision was made to impute all of the out-of-pocket health insurance premium costs. When MEPS interviewers collected information on medical expenses, they asked the respondents if they purchased their health insurance directly. If not, a questionnaire was sent to the source of insurance (typically the employer). This questionnaire asked how much the employer and employee paid for health benefits. At the time, it was thought that this information would be of very high quality. However, the response rate was **32%.**[8] As a result, the information on group health insurance plans was not released to the public. Also, the limited information on premiums for privately purchased plans was not used because of various problems in that information.[9]

Our match for premiums occurred between policyholders. In CE, the policyholder was not identified. CE gave information on the number of plans, type of plans and number of people covered by a specific plan. However, the CE does not associate plans with persons. Therefore, the policyholder was imputed before the match could take place. The observations were divided

---

[8] See Banthin (2001).

[9] To use all of the premium information that was collected, it is required to go to AHRQ's data center and to conduct the project there. They are set up similar to the Census's data centers. The information that was released on

into three groups: under 65 and group insurance, under 65 and privately purchased insurance and persons over 64.

If it was an employer provided plan, the assigned owner of the plan was the person who was working and had the highest education. If there was a tie, the oldest person was the planholder. If there was more than one group plan, the person selected first was not included as a potential recipient of "planholder" status. Then the plan would be assigned the same as the first plan, etc.

For privately purchased insurance, the policyholder was the person with the highest personal earned income. For people over 64 that had a private insurance plan, the planholder was chosen by education and then age. In both SIPP and MEPS, the policyholder is identified with the type of plan.

For each grouping of policyholders (employer provided, privately purchased, or over 64), the matching variables were slightly different. For group plans, the blocking variables were: 1) how much did the employer pay (none, some, all) 2) whether it was a family plan 3) whether the policyholder was in a professional or technical occupation 4) whether the policyholder was married 5) race/ethnicity 6) disability status and 7) living in an MSA. The "distance" variables were age, education, sex, family size, poverty status and region. They were given weights of 10, except for region with a weight of 5. CE's industry coding was not useful because of the way it was originally recoded for the public-use data.

For holders of private plans, the blocking variables were: 1) whether it was a family plan 2) whether the person worked, and if so, was it self employment 3) married 4) disability status and 5) race/ethnicity. With the exception of one variable, the distance variables were the same.

---

privately purchased plans also has problems and was released for use by researchers to develop "case studies." http://www.meps.ahrq.gov/Data_Pub/HC_FYData96.htm#hc017

The variable that indicated whether or not a person was in a technical or professional occupation was given a weight of 10.

For persons over the age of 64 that held private insurance, the blocking variables were: 1) married 2) disability status 3) sex 4) race/ethnicity and 5) MSA. The distance variables were the same as the ones in the group plan description except family size was not used.

The monthly premium for the plans was carried over to the recipient file. The monthly premium was multiplied by the months of coverage for that type of plan.